Cross-language Learning with Adversarial Neural Networks: Application to Community Question Answering

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Problem Definition

Overall goal: learn cross-language representation of the input for the target task in a unified framework

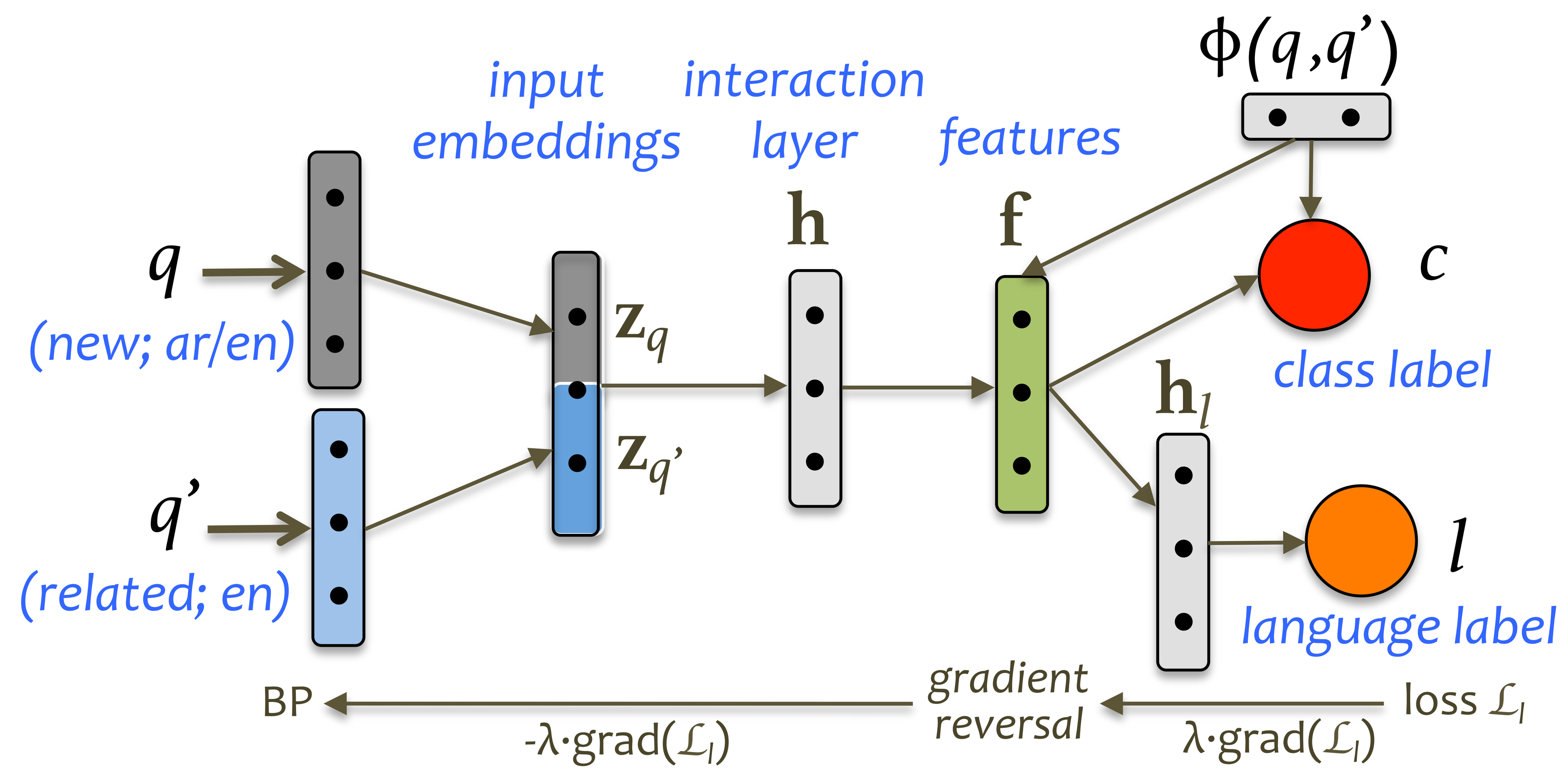
Cross-lingual question-question similarity scenario:

- Input:
  - a new user question q either in Arabic or in English
  - a set of potentially relevant existing questions $\{q'_k\}_{k=1}^{K}$, which are always in English
- Task: train a cross-lingual system to rerank $\{q'_k\}_{k=1}^{K}$ based on their similarity to q, where q is given in Arabic
- Approach:
  - train a binary classifier that decides whether q'_k is similar to q for a given pair of questions (q, q'_k)
  - use the posterior probability $p(c = 1|q, q'_k)$ for ranking
- Training scenarios:
  - *Unsupervised:* no class labels are given when q is in Arabic
  - *Semi-supervised:* some labeled examples available when q is in Arabic

Baseline Cross-lingual Model

- Use **cross-lingual embeddings** such as *bivec* (Luong et. al, 2015) to map q and q' to fixed-length vectors $\mathbf{z}_q$ and $\mathbf{z}_{q'}$
  - yields better initialization
  - crucial when there is no enough labeled data to learn the input representations with end-to-end training
- Model interactions between $\mathbf{z}_q$ and $\mathbf{z}_{q'}$:
  - $\mathbf{h} = g(U[\mathbf{z}_q; \mathbf{z}_{q'}])$
- Use pairwise features $\phi(q, q')$ to encode similarity directly:
  - $\mathbf{f} = g(V[\mathbf{h}; \phi(q, q')])$
  - $\phi(q, q')$ encode different similarity measures and task-specific features
  - A non-linear transformation allows us to learn high-level abstract features based on these pairwise features.
- The classification layer is defined by a sigmoid:
  - $\hat{c}_\theta = p(c = 1|\mathbf{f}, \mathbf{w}) = \mathrm{sigm}(\mathbf{w}^T[\mathbf{f}; \phi(q, q')])$
- We optimize the log probability:
  - $\mathcal{L}_c(\theta) = -c \log \hat{c}_\theta - (1 - c) \log (1 - \hat{c}_\theta)$
- This network learns features that are discriminative for the classification task, i.e., *similar* vs. *non-similar*. However, our goal is also to make these features invariant across languages.

Cross-Language Adversarial Neural Network (CLANN)



Adversarial Training

We put a **language discriminator**, another neural network that takes the internal representation of the network $\mathbf{f}$ as input, and tries to discriminate between *English* and *Arabic* q.

- The discriminator is defined by another sigmoid: $\hat{l}_\omega = p(l = 1|\mathbf{f}, \omega) = \mathrm{sigm}(\mathbf{w}_l^T \mathbf{h}_l)$
  - $\mathbf{h}_l = g(U_l \mathbf{f})$ defines the hidden layer of the discriminator
  - Discrimination loss: $\mathcal{L}_l(\omega) = -l \log \hat{l}_\omega - (1 - l) \log \left(1 - \hat{l}_\omega\right)$
- Overall training objective of the composite model:

$$\mathcal{L}(\theta, \omega) = \sum_{n=1}^{N} \mathcal{L}_c^n(\theta) - \lambda \Big[\sum_{n=1}^{N} \mathcal{L}_l^n(\omega) + \sum_{n=N+1}^{M} \mathcal{L}_l^n(\omega) \Big] \quad (1)$$

  where $\theta = \{U, V, \mathbf{w}\}$, $\omega = \{U, V, \mathbf{w}, U_l, \mathbf{w}_l\}$, and λ controls the relative strength of the two networks.
- In training, we look for parameters that satisfy a min-max optimization criterion:

$$\theta^* = \underset{U,V,\mathbf{w}}{\mathrm{argmin}} \max_{U_l, \mathbf{w}_l} \mathcal{L}(U, V, \mathbf{w}, U_l, \mathbf{w}_l) \quad (2)$$

  The updates of the shared parameters $\{U, V, \mathbf{w}\}$ for the two classifiers is done in an adversarial way.

Features

- Cross-language embeddings trained with `bivec` on parallel corpora (TED talks and OPUS)
- Similarity-based pairwise features:
  - Machine Translation measures: BLEU, NIST, TER, METEOR, unigram PRECISION, unigram RECALL, and components of BLEU
  - Cosine similarity between questions: using Google and QatarLiving word embeddings, and Syntactic embeddings from the Stanford parser
  - Task-specific features (Joty et al., 2015).

Dataset

Based on the SemEval-2016 Task 3 dataset

- 387 original questions (276, 50, and 70 for training, development and test)
- For each original question 10 related questions to be ranked
- We translated the 387 original questions manually to Arabic.
- We further collected 221 original and 1,863 related questions (English; unlabeled). We manually translated the 221 questions to Arabic.

Results

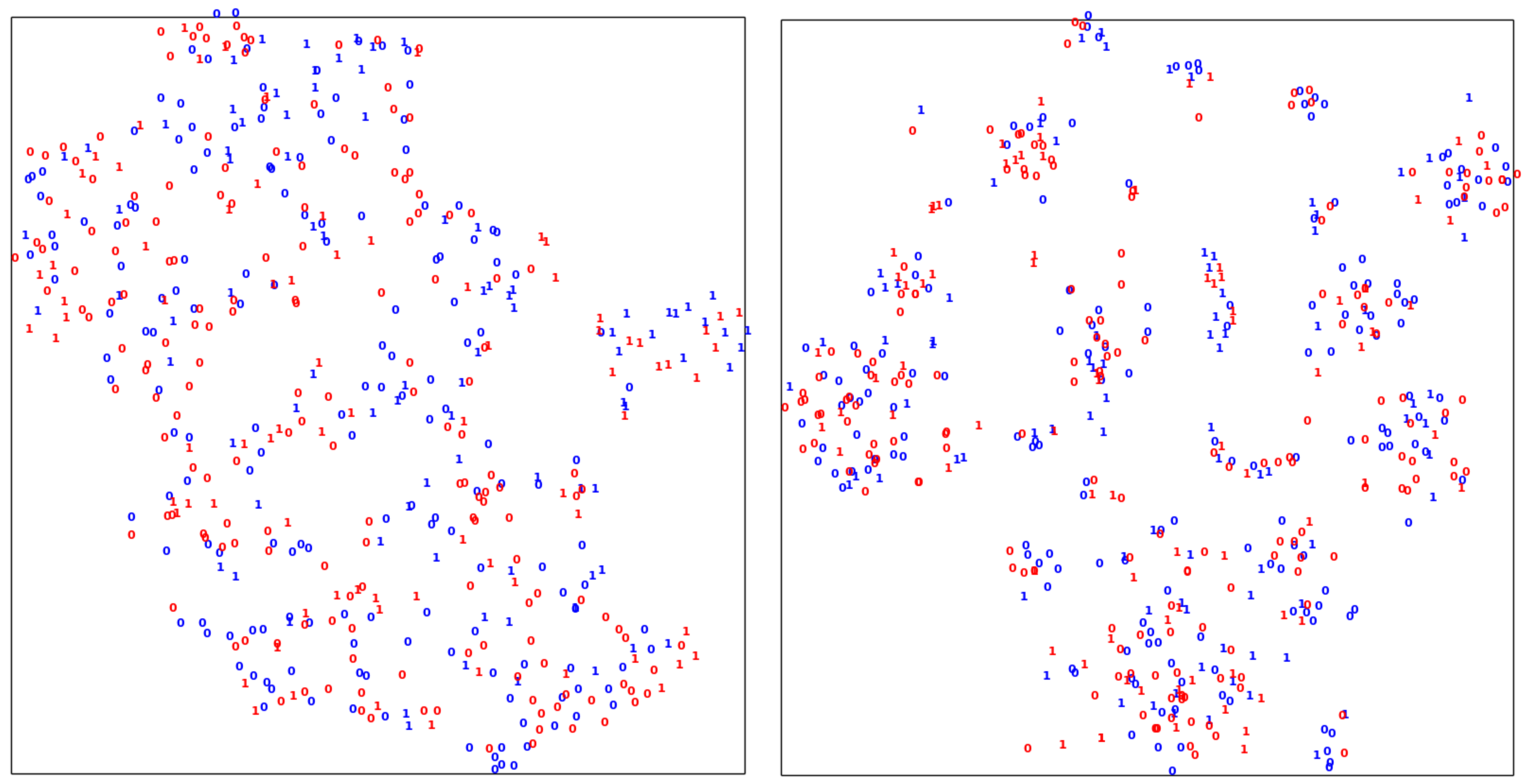
Unsupervised Adaptation

System		Discrim.	MAP	MRR	AvgRec
FNN	en→ar	–	75.28	84.26	89.48
CLANN	en→ar	en vs. ar'	**76.64**	**84.52**	**90.92**
FNN	ar→en	–	75.32	84.17	89.26
CLANN	ar→en	ar vs. en'	**76.70**	**84.52**	**90.61**

Semi-supervised Adaptation

System		Discrim.	MAP	MRR	AvgRec
FNN	en→ar	–	74.69	83.79	88.16
CLANN$_{unsup}$	en→ar	en vs. ar'	75.93	84.15	89.63
CLANN$_{semisup}$	en+ar*→ar	{en vs. ar*, en vs. ar'}	**76.65**	**84.52**	**90.84**

Visualizing the Representation Layer



Arabic=blue, English=red. Class labels {0,1}. L: ar→en, R: en→ar

Conclusion

We have studied cross-language adaptation for question-question similarity in community question answering, in order to port a system trained on one input language to another input language. This is novel in a cross-language setting.

Future work

- Fine-tune the word embeddings for the cross-language task
- Try LSTM and CNN
- Experiment with more than two languages at a time
- Apply to other tasks

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